# Thermal Image Based Fault Diagnosis of Gears using Support Vector Machines

**Anil Kumar, Deepam Goyal, B.S. Pabla**

***Abstract- Condition monitoring and fault diagnosis of working machines have gained significant attention due to their prospective benefits, such as enhanced productivity, decreased repair and maintenance costs and enhanced machine operation. In this paper, a thermal image based non-contact methodology has been proposed to diagnose the gear faults using support vector machines (SVM). The thermal images acquired from gearbox simulator were preprocessed using 2D-discrete wavelet transform to decompose the thermal images. The relevant features were extracted from converted thermal gray-scaled images followed by selecting the strongest feature using Mahalanobis distance criteria. Finally, the selected features were given to a SVM classifier for classifying the different gear faults. The experimental findings indicate that fault diagnosis using thermography for rotary machinery can be put into practice to industrial fields as a new smart fault diagnostic method with excellent prediction performance.***

***Keywords: Rotating machines, Thermal imaging, Support vector machines, Fault diagnosis.***

## I. INTRODUCTION

Condition monitoring of mechanical faults in rotating components is of great significance to provide a better product quality and ensure productivity and flexibility [1-2]. Most of these machines are operated with gears, bearings and other components that may become defective during their use and may influence the efficiency of the machine and may even result in the machine breakdown. Therefore, it is required to design systems capable of recognizing and handling different types of machine element failures to monitor the health of the machine aiding timely maintenance decisions.

Gears are considered as one of the key machine components in rotary machinery. Typical gear defects comprise root crack, surface damage, tooth breakage, wear, chipped teeth, wear and pitting [3-4]. These types of failure can lead to system imbalance and deterioration of machining accuracy. For the previous few decades, fault recognition has become a significant topic for comprehensive studies in order to diagnose various equipment faults. (42% of the total failures in gas turbines). Vibration monitoring has become an important technique in mechanical structural product's research, design, produce, application and maintenance [4]. Vibration analysis has been considered as the most prevalent method and widely examined and a variety of signal processing techniques comprising empirical mode decomposition [5], wavelet transform [6] and Hilbert transform [7] have also been formulated for diagnosing the inchoate defects in rotating machines. However, the signals acquired using vibration sensors are usually influenced by the choice of sensor positions and locations [8], harsh working environments such as greasy surface, high temperature and which introduces challenges on the installation of contact-type vibration sensors. An offline performed oil analysis method could detect debris in the lubrication system for fault diagnosis [9]. Unpredictable damage of gears and bearings may affect other rotating components of the machines and also enhance the asperity of the plant failure. Several techniques such as vibration monitoring, acoustic monitoring, wear debris analysis, motor current analysis, etc. have been reported in the literature for reviewing the gearboxes. Thermal Imaging Technique (TIT) is emerging as an alternative technique due to its non-intrusiveness, contactless and less complexity [10]. The thermal cameras sense radiation in a long-infrared range (9-14µm) of the electromagnetic spectrum and produce thermal images known as thermograms. As per Stefan-Boltzmann's law, temperature measurement depends on the intensity of the emitted radiation. TIT has been widely used in various engineering and non-engineering disciplines for condition monitoring and fault detection [11-12]. It is also used in manufacturing industries to detect serious faults in equipment, quality control and process control. In order to perform automatic health monitoring as well as fault diagnosis of the rotating machines using thermal imaging, four important stages are involved *viz.* image acquisition, image pre-processing, feature extraction and selection followed by classification. It is very important to understand the factors that contribute to the variations in the thermal behavior of the gears. In this work, these factors were studied by examining the thermal images of the region of interest of the gearbox diagnostic simulator machine. The mutual effects of thermal behavior and gear health conditions are analyzed accordingly. The characteristics of the temperature are stable to the type of fault, wear and tear and its severity [13]. Signal processing techniques utilized for extracting the statistical features of the temperature play an imperative role in the systems purported for the automated analysis and interpretation of bearing faults [14]. Hence, it is necessary to identify suitable signal processing techniques which can detect and categorize the fault accurately.

**Revised Manuscript Received on November 05, 2019.**

**Anil Kumar,** Department of Mechanical engineering, National Institute of Technical Teachers Training and Research, Chandigarh, India E-mail[1]: ak1992mech@gmail.com

**Deepam Goyal,** Department of Mechanical engineering, National Institute of Technical Teachers Training and Research, Chandigarh, India E-mail[2]: bkdeepamgoyal@outlook.com

**B.S. Pabla,** Department of Mechanical engineering, National Institute of Technical Teachers Training and Research, Chandigarh, India E-mail[3]: pablabs@nitttrchd.ac.in

In this study, the authors focus on designing one such automatic gear fault diagnosis framework capable of identifying healthy and faulty gear states using thermal images.

This paper is organised as follows: related work using thermal imaging techniques for the diagnosis of rotating machinery faults has been discussed in section II. Then, the experimental study of the gear fault diagnosis has been discussed in section III. In section IV, the training and testing procedure for SVM classifier has been introduced. The experimental results are presented in section V. Lastly the conclusion of the present work is described in section VI. Figure 1 presents the flow chart of the proposed methodology.

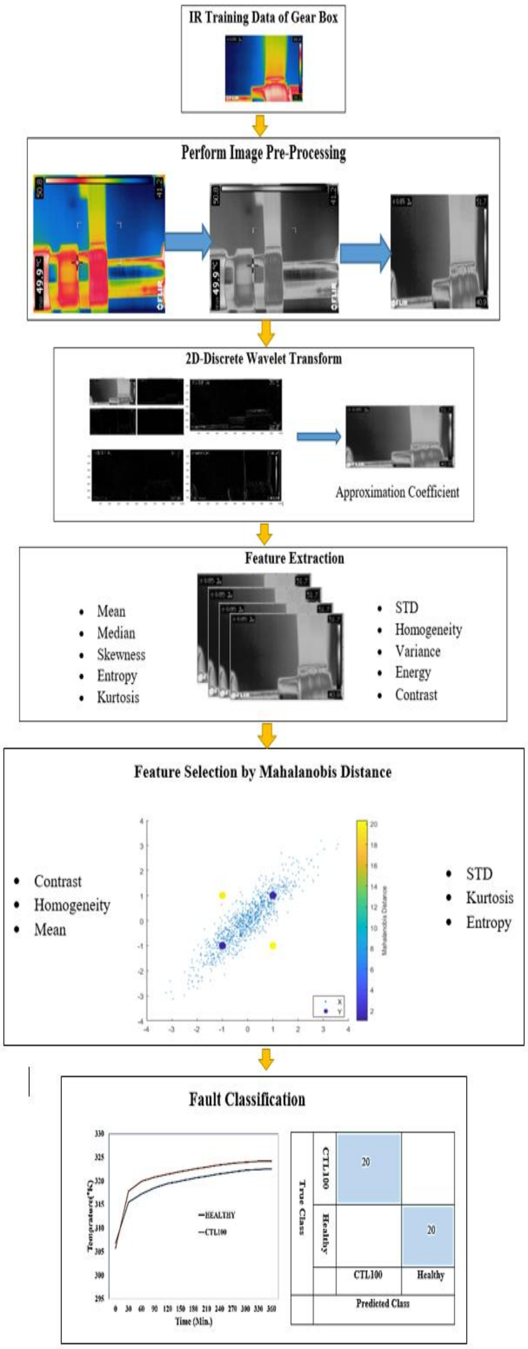


**Fig. 1. Flow diagram of the proposed methodology**

## II. THERMAL IMAGING AS DIAGNOSIS TOOL

The most important challenge in the diagnostics tool is to develop accurate and reliable thermal imaging techniques for identifying abnormalities and failures in a plant. Temperature signature is an important indicator and has the ability to provide an early warning to the technician or operator to make an intelligent decision before any critical problem occurs in the process or plant [15]. The amplitude of the temperature indicates a serious problem. The extraction of the signal from temperature measurement is challenging due to the presence of noise in the temperature signal or thermal image. TIT is the most prevalent tool to identify the degree and nature of any issues in rotating electrical machines and parts, such as rotor, gears and bearings or any maintenance choices identified with the machine.

The advancement in TIT has paved the way for the emergence of profitable techniques that have been extensively used for fault diagnosis of rotating electrical machines. In the past decennaries, enormous efforts have been dedicated to fault diagnosis of bearings in rotating electrical machinery established on thermal images. Younus and Yang [16] proposed a novel thermal-imaging based automatic fault diagnosis methodology to classify the different conditions of rotating machinery using a 2D-discrete wavelet transform (DWT). Mahalanobis distance and relief algorithm were applied to select the pertinent features for achieving a higher success rate. The selected features were further used as input vector for classifiers viz. SVM and linear discriminant analysis to categorize the different faults. Waqar and Demetgul [3] demonstrated a multilayer perceptron artificial neural network-based fault diagnosis approach to determine the condition of worm gear. It has been observed that the proposed strategy can be used to anticipate the oil level and speed of the gearbox and also notice the heating patterns for all those operating conditions. Garcia-Ramirez et al. [17] proposed a thermography image segmentation based approach for fault diagnosis of rotating machines. This methodology can identify the defects in bearings, broken bars in the rotor, misalignment, mechanical unbalance and also unbalance voltage in the incipient stage of fault in an induction motor. Nunez et al. [18] developed a low-cost TIT tool to identify the bearing failures in induction motor under different operating environments. The suggested approach is based on the thermal differential method to make the early detection of failure in changing environmental conditions. It has been inferred that an absolute thermogram is not enough to determine if a bearing is defective, it is necessary to consider the ambient temperature, by doing so this differential value is enough to detect the failure.

Janssens et al. [13] exhibited a new intelligent fault diagnosis methodology, containing two image-processing pipelines, to assess the condition of bearings using infrared thermography. The first pipeline focus on detecting the imbalances in the rotor by differentiating the consecutive image frames followed by summarizing their distribution along the axes of images. However, the second pipeline focus on detecting the bearing defects by introducing the three features namely the Gini coefficient, standard deviation and the moment of light. Glowacz and Glowacz [19] proposed an original approach i.e.

method of areas selection of image differences (MoASoID) to extract the thermal image-based features for monitoring the three different conditions (i.e. healthy motor, the motor with a defective ring of squirrel-cage and the motor with two broken bars) of induction motor. The proposed MoASoID was used to compare the different training sets together and to choose the regions with the biggest variations for the identification process. Klien et al. [20] proposed a thermal imaging based technique for analyzing and diagnosing the non-stationary time-frequency to RPM order representations (TFRs) of vibration-acoustic data, acquired from healthy and defective bearings. Lim et al. [15] developed an automatic fault diagnostic system based on features extracted from vibration signals and thermal images. SVM was employed to distinguish the machinery faults and it has been found that the success rate achieved with thermal image data is higher as compared to that obtained with vibration data.

## III. EXPERIMENTAL SETUP

This section describes the gear test rig and the experiments conducted for gear fault monitoring.

### A. Test Rig

An experimental setup, gearbox diagnostics simulator, was utilized to study defects in rotating machines. The experiment device had the purpose, especially as an academic study tool, to replicate industrial drive trains. Figure 2 shows the laboratory setup used to explore the faults of the machinery.

The test rig comprises of a single-parallel shaft gearbox with bearings and a computer-controlled magnetic brake. The components of the machine were arranged in such a way that a wide range of drivetrain configurations can be attained and used for experimentation. It was intended to manage heavy loads and was large enough to replace gears and to accommodate installation, set-up and tracking devices. The gears can be designed to alter the gear ratio as per requirement. It is also equipped with a variable frequency drive that controls the input shaft frequency. A built-in tachometer with one pulse per revolution analog transistor-transistor logic (TTL) output estimates the rotational shaft speed and also can be used to measure the transmission error. The specifications of the test rig are given in Table 1.

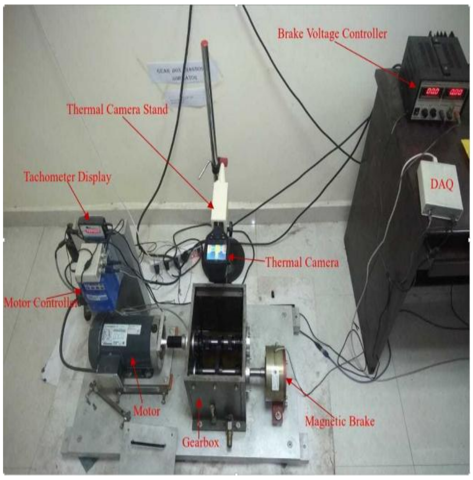


**Fig. 2 Test rig used for experimental measurements**

The parallel-shaft gearbox, consisting of input and output shafts, is a significant element of the rig and enables different kinds of research studies. Gears can slide along the shafts to change the rigidity of the structure and enable additional units to be mounted. The shafts were linked to the gearbox walls with bearing and bearing housing for flexible operation. The specifications of the gearbox are listed in Table 2.

**Table-I: Specifications of gearbox diagnostic simulator**

| PARAMETERS | VALUES |
|---|---|
| Manufacturer | Spectra Quest |
| VFD | Lenze |
| Motor | 3 HP, 3-φ |
| Rotational speed | 0 – 3000 rpm |
| External loading | Magnetic loading |
| Loading capacity | 0.126 N-m to 24.85 N-m |
| Gearbox speed reduction | Spur gear with single-stage speed reduction |
| Bearing | Deep groove ball bearing |
| Foundation | 2.7 mm die cast aluminium base with 8 rubber isolators |
| Weight (approx.) | 90.7 kg |
| Dimensions | L×B×H = 100 cm×50 cm×60 cm |

**Table-II: Specifications of gearbox**

| SPECIFICATIONS | VALUES |
|---|---|
| Dimensions | L×B×H = 27.5 cm×19 cm×26.5 cm |
| Length | 27.5 cm |
| Width | 19 cm |
| Height | 26.5 cm |
| Number of teeth on gear | 100 |
| Number of teeth on pinion | 29 |
| Centre distance b/w gears | 9.675±0.1 cm |
| Shaft diameter | 2.5 cm |
| Reduction ratio | 3.44:1 |
| Pressure angle ($\alpha_p$) | 20° |

Figure 3 shows the gear's conditions with different severity of faults. Experiments were conducted on the GDS machine at different loading (no-load and 10.5 Nm) and running (1600, 1800 and 2000 rpm) using two gear samples i.e. healthy gear (H) and gear with 100% chipped tooth (CTL100).

An adjustable stand for holding the thermal imaging camera has been made using a rapid prototyping machine. The thermal camera was set at the fixed distance of 30 cm above the gearbox to acquire the thermal signatures at the interface of rotating spur gear.

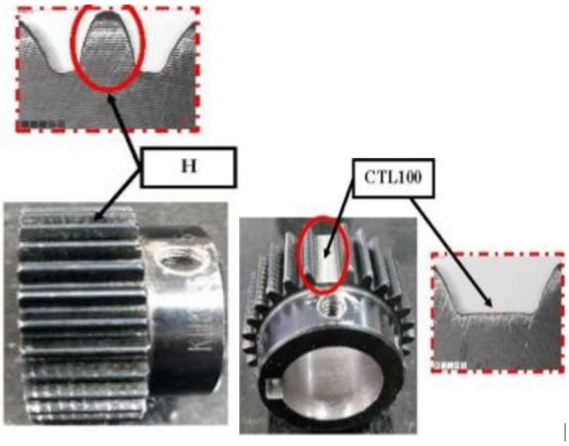


**Fig. 3: Spur gears with different severity of faults**

## IV. SVM Training and Testing

This section describes the proposed methodology adopted for gear fault detection and classification using 2D-DWT, Mahalanobis distance and SVM Classifier.

### A. Discrete Wavelet Transform

DWT has high performance and attains good ranks among the best decomposition techniques [13]. It can perform multi-resolution analysis in both frequency and time domain. The second decomposition level of the DWT was applied to the thermal images collected from gearbox under different operating conditions. The four types of wavelet coefficients namely (vertical coefficients, horizontal coefficients or detailed components, diagonal and approximation coefficients) were obtained from each image. The 2D-DWT decomposes an image at each level providing four sub-images i.e. low-resolution (LL) and three coefficient (HL, LH, HH) sub-images. The scale of the raw image (Io) at k = 0 can be set to 2k = 20 = 1. In addition, the sub-images at k = 1 can be represented as;

$$w_{01}(a,b) = \left[L_x * \left[L_y * I_o\right]\downarrow_2\right]\downarrow_2 (a,b) \qquad (1)$$

$$w_{11}(a,b) = \left[L_x * \left[H_y * I_o\right]\downarrow_2\right]\downarrow_2 (a,b) \qquad (2)$$

$$w_{21}(a,b) = \left[H_x * \left[L_y * I_o\right]\downarrow_2\right]\downarrow_2 (a,b) \qquad (3)$$

$$w_{31}(a,b) = \left[H_x\left[H_y *\right]\downarrow_2\right]\downarrow_2 (a,b) \qquad (4)$$

Where (↓) and (*) represents the down-sampling and convolution processes respectively. Here *($H_x$, $H_y$)* and *($L_x$, $L_y$)* are high-pass and low-pass filters. Figure 4 depicts the data processing procedure using discrete wavelet transform.

The filtering and down sampling process for $w_{(01)}$ can be written as,

$$Y_{low}(a,b) = \left[L_y * I_o\right]\downarrow_2 (a,b) = \sum_{j=-2}^{1} I_o(a,j) L_y(a, 2b-j), \qquad (5)$$

$$w_{01}(a,b) = \left[L_x * \left[L_y * I_o\right]\downarrow_2\right]\downarrow_2 (a,b)$$

$$\sum_{j=-2}^{1} Y_{low}(j,b) L_x(2a-j, b), \qquad (6)$$

Similar steps are performed to attain $w_{11}$, $w_{21}$ and $w_{31}$.

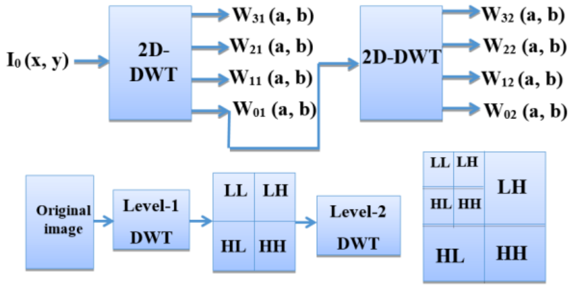


**Fig. 4: Data processing procedure for two-dimensional DWT**

### B. Feature extraction

The image features, including boundary, zone, pixels and texture-based information, may be estimated and extracted by a number of various approaches. In this work, 11 features, namely, contrast, correlation, energy, homogeneity, mean, median standard deviation, skewness, kurtosis, entropy and variance were extracted on the 2D approximation coefficient image computed according to DWT [13]. These are extracted using thermal images obtained from the gearbox for different gear and operating conditions. In each condition, a total of twenty-four samples of the thermal images acquired in each condition of gear were collected.

### C. Feature selection

The extracted features were then selected using the Mahalanobis distance (MD) criterion to enhance the classification accuracy. MD has been recognized as one of the most popular measures that can be used to establish if a data sample is an element of a category or not and defined as the distance between two points in multivariate space [16]. It is given as:

$$MD = [(a-b)C\text{^}(-1)(a-b)] \qquad (7)$$

Where a, b: points from the same distribution; C: covariance matrix; MD: Mahalanobis distance. The distances between all the extracted features are computed using MD criterion. After determining MD, the mean distances of all features for different conditions were estimated and subsequently, 6 relevant features, namely, contrast, homogeneity, mean, Standard deviation, kurtosis and entropy have been selected in accordance with the level of relevance.

### D. Support vector machines

The self-adaptive fault diagnosis system has to automatically discriminate between different gear defect conditions without human intervention for result interpretation. SVM is a supervised learning algorithm that can be used for both regression challenges and classification [21]. SVM is shown to be more effective for thermal imaging-based fault diagnosis than other learning techniques due to risk depreciation with higher accuracy for rotating machines [16]. The main objective of SVM is to make a multi-dimensional hyperspace with the selected features and then draw an optimal hyperplane to divide into different gear defects. In this work, SVM classifier was applied to classify the two different gear conditions.

For each gear condition, a total of 20 thermal images were captured at two loading and three running conditions. Therefore the total number of thermal images was 240 (20*3*2*2). The performance of the proposed approach is validated for individual loading conditions, i.e. each data set considers 120 images which is divided into two groups, training and testing data sets. Fig. 5 and Fig. 6 illustrate the thermal images of different faulty conditions of gear and experimental setup respectively.

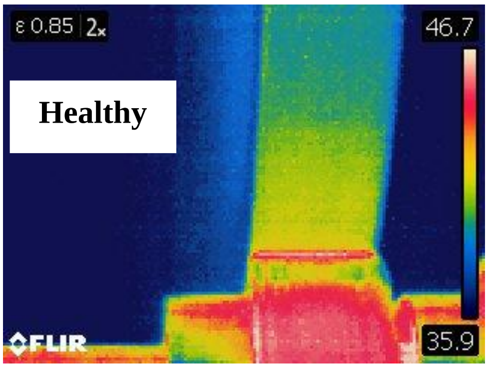


**Fig. 5: Thermal image of healthy gearbox at 10.5 Nm load and 2100 RPM**

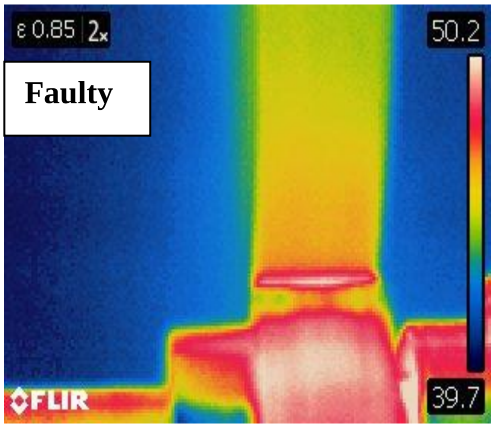


**Fig. 6: Thermal image of faulty gearbox at 10.5 Nm load and 2100 RPM**

## V. RESULTS

In the proposed analysis, thermal images are measured under laboratory conditions. At the ambient temperature, the gearbox simulator is switched ON. Its thermal signature starts increasing from its ambient temperature to a higher value steady state. Thermal images were acquired from the test rig under operating and gear conditions. The acquired signatures were firstly decomposed using 2D-DWT followed by the feature extraction. The approximation coefficient was considered since the most prominent information has been contained in a low-frequency signal in the original thermal image.

Figure 7 shows that the steady-state temperature was achieved after 6 hours of gearbox operation. The thermal signature of healthy gear is lower than the faulty one. However, the temperature difference between the healthy and faulty gear has been found to decrease with the increase in time.

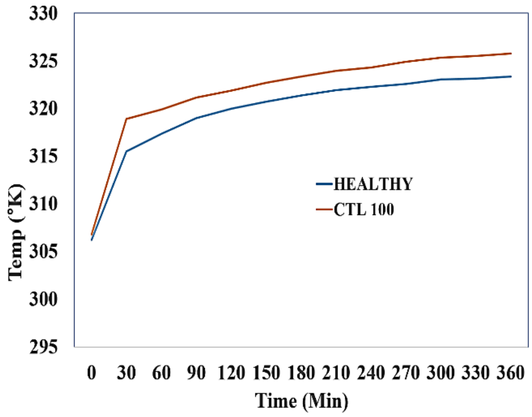


**Fig. 7. Thermal performance curves comparison of healthy and CTL100 gears**

Six strongest features (out of eleven) were finally selected using the Mahalanobis distance criterion. An input vector was constructed, using these selected features, to be given to different SVM algorithms. The classification accuracy obtained using different SVM training function has been given in Table 3. It has been noticed that Linear SVM outperforms other algorithms with a success rate of 100%.

**Table III. Classification accuracy obtained using different SVM algorithms**

| Algorithm | Accuracy (%) |
|---|---|
| Linear | 100 |
| Quadratic | 99.7 |
| Cubic | 98.3 |
| Fine Gaussian | 97.5 |
| Medium Gaussian | 99.2 |
| Coarse Gaussian | 98.3 |

The confusion matrix obtained for different gear conditions is given in Table 4. It can be seen that the proposed methodology can classify the different gear conditions accurately. In all the scenarios, faulty conditions were identified from a healthy bearing condition. Therefore, it can be stated that the proposed intelligent thermal-imaging based fault diagnosis and monitoring system can classify and diagnose the thermal images of faulty and healthy conditions of gear with higher classification accuracy on the experimental dataset.

**Table IV: Confusion matrix obtained for healthy and faulty gear using SVM**

| | | Predicted class | |
|---|---|---|---|
| True class | | CTL 100 | Healthy |
| | CTL 100 | 20 | 0 |
| | Healthy | 0 | 20 |

## VI. CONCLUSION

In the present study, the gear fault diagnosis has been accomplished using SVM based on thermal signatures. The data has been acquired experimentally from a gearbox dynamic simulator machine under different operating and gear conditions.

The acquired data was pre-processed using 2D-DWT followed by extraction and normalization of features. Mahalanobis distance criteria was employed to elect the most relevant features for reducing the computation complexity and improving the classifier performance.

It was observed that the Linear-SVM based classification outperformed the other SVM kernel functions with a 100% success rate. The experimental results demonstrate that fault diagnosis using thermography for rotary machinery can be applied to industrial fields as a new smart fault diagnostic method with excellent prediction performance. The research work can be further extended by using additional suitable fault indicators and different types of more advanced classification algorithms.

**Conflict of Interest Statement**

It is stated that the authors have no conflict of interest.

## REFERENCES


1. Goyal, D. and Pabla, B.S., 2016. The vibration monitoring methods and signal processing techniques for structural health monitoring: a review. Archives of Computational Methods in Engineering, 23(4), pp.585-594.
2. Randall, R.B. and Antoni, J., 2011. Rolling element bearing diagnostics-A tutorial. Mechanical systems and signal processing, 25(2), pp.485-520.
3. Waqar, T. and Demetgul, M., 2016. Thermal analysis MLP neural network based fault diagnosis on worm gears. Measurement, 86, pp.56-66.
4. Goyal, D., Pabla, B.S. and Dhami, S.S., 2017. Condition monitoring parameters for fault diagnosis of fixed axis gearbox: a review. Archives of Computational Methods in Engineering, 24(3), pp.543-556.
5. Lei, Y., Lin, J., He, Z. and Zuo, M.J., 2013. A review on empirical mode decomposition in fault diagnosis of rotating machinery. Mechanical systems and signal processing, 35(1-2), pp.108-126.
6. Wang, J., Gao, R.X. and Yan, R., 2014. Multi-scale enveloping order spectrogram for rotating machine health diagnosis. Mechanical Systems and Signal Processing, 46(1), pp.28-44.
7. Osman, S. and Wang, W., 2013. An enhanced Hilbert–Huang transform technique for bearing condition monitoring. Measurement Science and Technology, 24(8), p.085004.
8. Goyal, D., Pabla, B.S. and Dhami, S.S., 2019. Non-contact sensor placement strategy for condition monitoring of rotating machine-elements. Engineering Science and Technology, an International Journal, 22(2), pp.489-501.
9. Prabhakaran, A. and Jagga, C.R., 1999. Condition monitoring of steam turbine-generator through contamination analysis of used lubricating oil. Tribology International, 32(3), pp.145-152.
10. Bagavathiappan, S., Lahiri, B.B., Saravanan, T., Philip, J. and Jayakumar, T., 2013. Infrared thermography for condition monitoring–A review. Infrared Physics & Technology, 60, pp.35-55.
11. Maldague, X., 2001.Theory and Practice of Infrared Technology for Non-Destructive Testing, John Wiley-Interscience, pp. 684.
12. Ring, E.F.J. and Ammer, K., 2012. Infrared thermal imaging in medicine. Physiological measurement, 33(3), p.R33.
13. Janssens, O., Schulz, R., Slavkovikj, V., Stockman, K., Loccufier, M., Van de Walle, R. and Van Hoecke, S., 2015. Thermal image based fault diagnosis for rotating machinery. Infrared Physics & Technology, 73, pp.78-87.
14. Jardine, A.K., Lin, D. and Banjevic, D., 2006. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical systems and signal processing, 20(7), pp.1483-1510.
15. Lim, G.M., Bae, D.M. and Kim, J.H., 2014. Fault diagnosis of rotating machine by thermography method on support vector machine. Journal of Mechanical Science and Technology, 28(8), pp.2947-2952.
16. Younus, A.M. and Yang, B.S., 2012. Intelligent fault diagnosis of rotating machinery using infrared thermal image. Expert Systems with Applications, 39(2), pp.2082-2091.
17. Garcia-Ramirez, A.G., Morales-Hernandez, L.A., Osornio-Rios, R.A., Benitez-Rangel, J.P., Garcia-Perez, A. and de Jesus Romero-Troncoso, R., 2014. Fault detection in induction motors and the impact on the kinematic chain through thermographic analysis. Electric Power Systems Research, 114, pp.1-9.
18. Nunez, J.A.R., Velazquez, L.M., Hernandez, L.A.M., Troncoso, R.J.R. and Osornio-Rios, R.A., 2016. Low-cost thermographic analysis for bearing fault detection on induction motors, 75, pp. 412-415.
19. Glowacz, A. and Glowacz, Z., 2017. Diagnosis of the three-phase induction motor using thermal imaging. Infrared physics & technology, 81, pp.7-16.
20. Klein, R., Masad, E., Rudyk, E. and Winkler, I., 2014. Bearing diagnostics using image processing methods. Mechanical systems and signal processing, 45(1), pp.105-113.
21. Widodo, A. and Yang, B.S., 2007. Support vector machine in machine condition monitoring and fault diagnosis. Mechanical systems and signal processing, 21(6), pp.2560-2574.


## AUTHOR PROFILE

**Anil Kumar**, ME Scholar (Mechanical Engineering) National Institute of Technical Teachers Training and Research, Chandigarh, India. Areas of interest:- Machine Learning, Automobiles and Transmission system. ak1992mech@gmail.com, Contact No:- +919784277409.